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ANALYSIS OF INFLUENCE OF POWER QUALITY DISTURBANCES USING A NEURO-FUZZY SYSTEM

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ABSTRACT
The authors propose an automated neuro-fuzzy system approach (with neural network subsystem) to power quality assessment incorporating equipment susceptibility patterns. The system is expected to handle dependencies between superposition of different disturbances and specific devices' susceptibility to disturbances. Two neural network architectures were applied: a well known radial-basis neural networks for automatic rules' generation and a neuro-fuzzy system for overlaid disturbances influence modeling. Proposed approach can help to predict damages or abnormal functioning of devices and implement adequate countermeasures.

KEY WORDS
Neural Networks, Fuzzy Logic, Power Quality

1. Introduction

The growing interest in power quality (PQ) should be viewed in a context of recent developments in electrical power engineering. Increased attention, paid to PQ by the industry and scientific community, has many reasons [1-3]: The deregulation of the electricity market has caused growing need for standardization and performance criteria. Electrical energy is a product on a free market, with certain parameters which should be held within limits. Electronic and power electronic equipment has become more sensitive to voltage disturbances than its counterparts in the past. Malfunction of a control system due to power quality disturbances may cause significant financial losses.

Modern power electronic equipment as well as other non-linear devices are not only sensitive to voltage disturbances but also cause disturbances themselves. Finally, not only customers, but also internal phenomena in the supply system, can lead to PQ deterioration. Additionally, from the point of view of PQ, the power grid can be seen as a source and interconnections between disturbances' sources and sinks.

The ideal voltage curve in a three-phase electrical power network should be characterized as follows [4]: sinusoidal waveform, constant frequency according to the grid frequency, equal amplitudes in each phase according to the voltage level, defined phase-sequence with an angle of 120° between them. Every phenomenon affecting those parameters will be seen as decrease in voltage quality.

Allowed disturbances levels and acceptable signal parameters are defined in relevant standards [5,6].

Automated PQ monitoring methods have been proposed in [7,8] for efficient processing of a large number of data. It should be stressed that it is not always necessary to install sophisticated compensation devices, because the load in question does not suffer from disturbances even higher then allowed. On the contrary, a certain superposition of different disturbances which are within limits given in standards may cause damage to appliances.

In this paper we use a method for power quality assessment applying Neuro-Fuzzy system to handle dependencies between superposition of different disturbances and specific devices' susceptibility to disturbances.

Neuro-fuzzy systems have the ability do learn and to adapt [9], so they seem flexible enough to deal with such complex problem. The theory of fuzzy sets is exploited to explore the influence of different disturbances on equipment and mutual relations between different disturbances. Two neural network architectures were applied: a well known radial-basis neural networks and a neuro-fuzzy system. The detailed description of applied neural and neuro-fuzzy systems can be found in [9-14].

2. Experiments and Discussion

The scope of research was to find a flexible tool, capable of learning different sensibility patterns. This capability is important for further practical implementations in different environments. For the initial research the sensibility of devices was defined according to arbitrary rules. In practice it should be determined in accordance with measurements of disturbances levels and devices' malfunctioning rate.

Fuzzy sets theory was exploited for overlaid disturbances influence modelling. Fuzzy inference system should distinguish between normal and abnormal condition of a power supply system (good and poor power quality). In uncertain cases there should be a proper indication of a "danger" situation, which could lead to improper operation or damage.

Verification of neuro-fuzzy system applicability for power quality assessment was done on a broad spectrum of power quality indices variation and for different equipment sensibility patterns.

2.1 Patterns with voltage variations

In this section, equipment susceptible to voltage sags and swells was investigated. It was assumed, that other phenomena do not have significant influence on devices' operation.

Power Quality disturbances were chosen according to the EN 50160 standard [6]. Table 1 shows names and arbitrary selected change ranges of parameters, which were registered for every 10 min. period. In other words, for every 10 min. observation period a vector consisting of five values used as input to neuro-fuzzy system was constructed.

As the standard [6] allows voltage level variation of U_n ±10%, it was assumed that voltage variation of 7 % and more is considered as *high*. Sags and swells were defined as voltage variation exceeding 10 %. To simplify the decision process only the number of occurrences in 10 min. time window was registered. On the other hand, frequency of occurrences is also important to proper operation of equipment, so three stages of phenomenon severity were introduced: *allowed, medium, high*. Fig. 4 illustrates examples of highest and Fig. 5 of lowest voltage values in every 10 min. time window.

Table 1. Selected Power Quality Disturbances

Disturbance Name	**Disturbance level**		
	allowed	medium	high
voltage level	0-7 %	-	7-10 %
sag	0-4	5-7	8-10
swell	0-4	5-7	8-10
frequency	0-0.7 %	-	0.7-1.0 %
harmonics	0-8 %	-	8-10 %

In real applications, the equipment susceptibility is defined through matching of abnormal system operation (system damage) and power quality disturbance levels. Fuzzy rule building is done by a neural network (RBNN) subsystem.

In the described case, the equipment properties were also detected and learned by neuro-fuzzy system. Additionally, the susceptibility was predefined and can be arbitrarily described as follows: If swells or sags are *high* (for details see Table 1) abnormal operation is expected. If swell and sags are *medium* and other disturbances *allowed* also an abnormal operation is expected. If swell is *medium* or sag is *medium* and other disturbances are *high* abnormal operation is expected, as well. If swell and sag are *allowed* and other disturbances are *high* there is no threat.

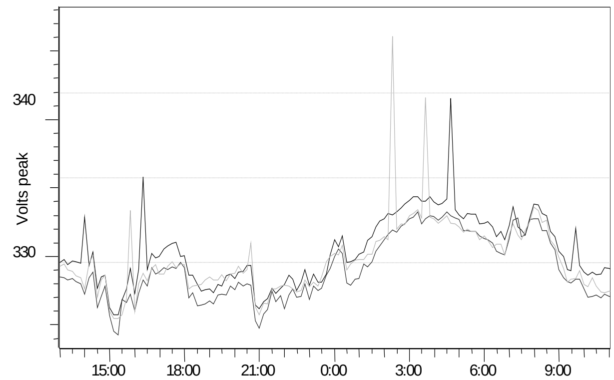

Fig. 1. Voltage peaks within 10 min. periods (maximal values).

Experiment results are shown in Table 2. The neuro-fuzzy system was trained with 2000 training vectors consisting of 5 random values describing the disturbances within a 10 min. time window (Table 1) and one discrete output value – "0" or "1".

The output value was selected according to the predefined equipment susceptibility; the neuro-fuzzy system is however expected to give continuous output vales. "1" stands for "equipment malfunction or damage", "0" should be interpreted as "normal operation". Values near "1" mean "near-abnormal operation or damage". The lower the output value the smaller the probability of a malfunction.

Test input vectors and respective outputs are summarized in Table 2. In case 2 swells were severe, so the system output is close to 1. In case 3 only sags were on the level *high* (Table 1) and swells were low, so the system output – 0.82- can be correctly recognized as "near-malfunction or damage". Case 5 is very similar to case 2, only sags are in *high* range. In case 19 sags and swells are *medium* and other disturbances are *low* or *medium*, so the output equals 0.51 – "low risk of damage". Case 21 is similar. In the same manner other neuro-fuzzy outputs can be interpreted. Most of the cases have been correctly recognized and interpreted by the neuro-fuzzy system. It is matter of discussion, how some incorrect outputs can be "corrected" by e.g. better training scheme.

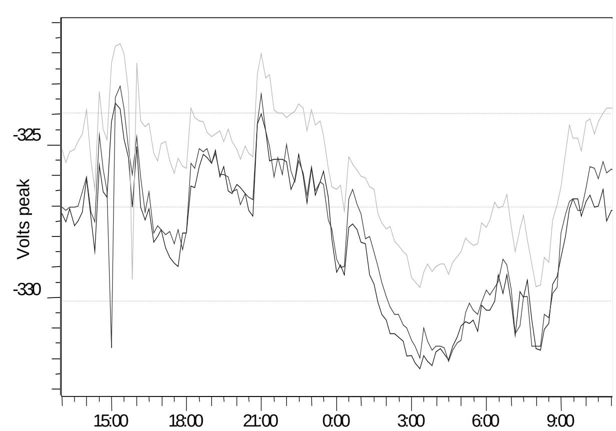

Fig. 5. Voltage peaks in 10 min. periods (minimal values)

Table 2. Neuro-fuzzy system answers

No.	sag [No.]	swell [No.]	frequency [%]	voltage level [%]	harmonics (THD) [%]	Discrete train. value	N.-F. output
1.	3	9	0.60	7.19	9.73	1	1.01
2.	0	10	0.92	5.44	7.22	1	1.11
3.	8	1	0.76	6.02	9.83	1	0.82
4.	8	5	0.58	7.69	7.91	1	0.8
5.	10	5	0.60	3.1	9.09	1	1.1
6.	8	7	0.19	5.4	3.33	1	0.94
7.	5	1	0.73	6.41	6.91	0	0.08
8.	3	1	0.06	7.71	5.77	0	-0.13
9.	2	4	0.67	7.13	2.42	0	-0.03
10.	1	2	0.61	6.16	4.61	0	-0.13
11.	3	1	0.20	3.07	9.36	0	-0.1
12.	6	1	0.24	6.5	0.59	0	0.21
13.	4	3	0.49	8.42	6.42	0	-0.01
14.	1	5	0.61	6.81	2.16	0	0.04
15.	3	4	0.33	2.26	2.06	0	0.01
16.	7	4	0.02	4.69	7.34	0	0.5
17.	2	7	0.11	8.84	5.28	0	0.46
18.	7	4	0.07	5.02	8.56	0	0.49
19.	7	4	0.72	0.27	4.07	0	0.51
20.	5	5	0.82	6.71	9.91	1	0.31
21.	5	7	0.78	9.76	8.11	1	0.64
22.	4	8	0.67	2.31	2.35	1	0.78

The main advantage of this approach to power quality assessment is the reduction of data to be analyzed by a human system operator. The neuro-fuzzy analyzer matches logically five different indices and gives as output one value describing the possible threat to electrical equipment.

2.2 Patterns with transients and higher harmonics

Verification of neuro-fuzzy system flexibility and adaptability to equipment susceptibility patterns was tested using patterns with transients and higher order harmonics (e.g. capacitor banks, instrument transformers). The number of input values was intentionally reduced to four: 19th and 21st harmonics (H_{19}, H_{21}), total harmonic distortion (THD) and number of overvoltages.

Table 3 shows names and arbitrarily selected variation ranges of input parameters, which were registered for every 10 min. period and correspond to standard [6].

Table 3. Selected Power Quality Indices

Disturbance Name	**Disturbance level**		
	allowed	medium	high
19th harm. level	0-1.0 %	1.0-1.5%	1.5-2.0%
21st harm. level	0-0.3%	0.3-0.5%	0.5-0.9%
THD	0-8%	-	8-15%
overvoltages	0-9	10-17	18-30

As in the previously described experiment, the equipment susceptibility was predefined and can be described as follows: If 19th harmonic or 21st harmonic are *high* (for details see Table 3) then the abnormal operation is expected. If two disturbances from three (H_{19}, H_{21}, overvoltages) are *medium* level, then abnormal operation is expected. If one disturbance from three (H_{19}, H_{21}, overvoltages) is *medium* and THD is *high* then the abnormal operation is expected, as well. On the contrary, if THD is *high* and H_{19}, H_{21}, overvoltages are *allowed* - normal operation is expected.

Investigation results are shown in Table 4. As before, most cases were correctly recognized, accordingly to the learning patterns (Table 4, cases 1..12). However, in some situations (e.g. case 13) there was a discrepancy between the neuro-fuzzy system output and discrete learning pattern. In case 13 THD was *allowed,* overvoltage *allowed*. Because H_{19} was *medium* (lower bound) and H_{21} *medium* (in the middle between limits) the system output was 0.62. This value can be correctly interpreted as "dangerous but not disastrous, no immediate damage". Due to the properties of fuzzy system the value of 0.62 is more adequate (H_{19}, H_{21} values are moderate), than 1.00 in the strict sense of equipment susceptibility pattern description. Further cases show no interpretation difficulties.

Table 4. Neuro-fuzzy system answers

No.	H_{19} [%]	H_{21} [%]	overvoltage [No.]	THD [%]	Discrete train. value	N.-F. output
1	1.33	0.56	30	2.16	1	1.00
2	1.47	0.19	26	8.15	1	1.04
3	1.63	0.43	7	13.89	1	1.02
4	0.91	0.31	23	1.13	1	0.92
5	0.07	0.53	2	12.60	1	1.03
6	0.55	0.74	25	13.98	1	0.97
7	0.98	0.07	6	5.58	0	0.09
8	0.81	0.25	7	2.74	0	0.05
9	0.04	0.03	9	6.38	0	0.03
10	0.35	0.35	4	0.99	0	0.12
11	0.08	0.12	9	1.09	0	-0.00
12	0.83	0.11	1	6.26	0	-0.06
13	1.07	0.43	6	1.55	1	0.62
14	0.46	0.27	11	14.69	1	0.61
15	1.20	0.34	2	5.83	1	0.53
16	1.16	0.31	8	1.80	1	0.46
17	0.35	0.09	8	10.47	0	0.30
18	1.10	0.30	6	6.64	0	0.37
19	1.24	0.25	3	4.63	0	0.49
20	0.37	0.11	15	2.95	0	0.54

The neural networks were trained with 1000 training vectors consisting of 4 random values describing the disturbances in 10 min. time window and one discrete output value – "0" or "1". The output value "1" stands for "equipment malfunction or damage", "0" should be interpreted as "normal operation". Values near "1" mean "near-abnormal operation or damage". The lower the output value the smaller the possibility of malfunction.

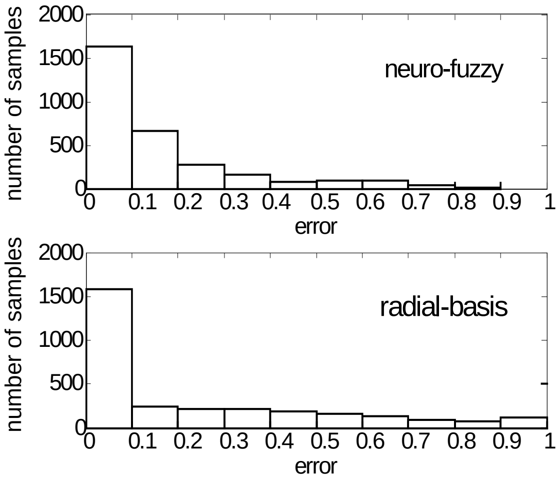

Fig. 2. Histograms of errors of classification.

In this section, the results obtained using radial-basis neural network and for neuro-fuzzy system for the same task were compared. The criterion was the difference between predefined value “0” or “1” and the network output value. This difference could be defined as the error of classification for all input values. In comparison to neuro-fuzzy networks the radial-basis network delivered larger values of both maximum error and sum of square of errors. Figure 5 shows the histogram of errors for 3000 input vectors (samples).

The histograms indicate that errors as high as one were generated by radial basis network. For that reason neuro-fuzzy network has been chosen for the main part of investigations.

3. Conclusion

The neuro-fuzzy system applied for PQ problem was able to construct “if-then” rules without an expert knowledge, only using training vectors containing measured values and desired output.

Fuzzy logic enables non discrete reasoning and proper indication of “in-between” cases and “near-damage” situation. For power quality assessment it seems to be more advantageous than “0-1” logic.

The neuro-fuzzy system has useful adaptation ability. It may be applied for different susceptibility patterns of equipment and different number of disturbances (input values) to be matched.

Important advantage of this approach to power quality assessment is the reduction of data to be analyzed by a human system operator. The neuro-fuzzy analyzer matches logically different indices and gives as output one value describing the possible threat to electrical equipment.

Disadvantageous is the learning process, for which quite large amount of training vectors is required (ca. 1000, the more is better). In some ceases the neuro-fuzzy output can not be clearly interpreted, but such conditions are rare and does not overshadow the generally right reasoning of such system.

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